Departamento de
Dirección de Empresas

Working paper series

WP BSAD 11.07

ACADEMIC QUALITY MEASUREMENT: A MULTIVARIATE APPROACH

December 2011

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Abstract

This paper applies a new quality measurement methodology to measure the quality of the postgraduate courses. The methodology we propose is the Academic Quality Measurement (AQM). The model is applied to several simulated data sets where we know the true value of the parameters of the model. A nonparametric model, based in Nearest Neighbours combined with Restricted Least Squared methods, is developed in which students evaluate the overall academic programme quality and a set of dimensions or attributes that determine this quality. The database comes from a Spanish Public University post graduate programme. Among the most important conclusion we say the methodology presented in this work has the following advantages: Knowledge of the attribute weights allow the ordering of the attributes according to their relative importance to the student, showing the key factors for improving quality. Student weights can be related to student characteristics to make market segmentation directly linked to quality objectives. The relative strengths and weaknesses of the service (high educations) can be determined by comparing the mean value of the attributes of the service to the values of other companies (Benchmark process or SWOT analysis).

Keywords: Quality Measurement, Postgraduate Programme, Nonparametric Model.

ACADEMIC QUALITY MEASUREMENT: A MULTIVARIATE APPROACH

1. Introduction

Quality service has come to be recognized a strategic tool for attaining operational efficiency and improved business performance (Hendrick et al, 2001; Seth, Deshmukh and Vrat, 2005). Several authors have discussed the importance of quality to service firms (Cook Goh and Chung, 1999; Normann, 1984; Horovitz, 2001; Parasuraman, 2002) and have demonstrated its strong relationship with profits, increased market share, return on investment (ROI), customer satisfaction, and future purchase intentions (Anderson, Fornell and Lehmann 1994; Boulding et al., 1993; Buzzell and Gale, 1987; Rust and Oliver, 1994; Llusar et al, 2001). One direct conclusion of these studies is those firms with superior quality outperform those marketing inferior quality (Zemke, 1999; Gustafsson et al, 2003; ASCI, 2008).

The assessments of the higher education, as an important service from the point of view of the governments and citizens and since there resource's shortages, gain importance. Higher education is passing through a period of re-organization and re-establishment of new principles. According to Bologna Accord the *European Higher Education Area* (EHEA) was created "by making academic degree standards and quality assurance standards more comparable and compatible throughout Europe" and the publication of *Tuning Educational Structures in Europe*. In Spain the *National Quality and Accreditation Evaluation Agency (ANECA*) have developed different ways to improve the quality of the education.
As we can see, both at European and National levels, the issue of educational services quality is brought forward, taking into consideration the fact that universities are approached as socio-economical entities which objective is the survival in a competitive environment Quality tools become a good option in this situation.

The attention being devoted to the measurement and evaluation of the quality of postgraduate programs, particularly of Masters programs, and of students' satisfaction with these programs, is quite a new fact [Dubas, Ghani and Strong, 1998; Marks, 2001; Martin and Bray, 1997; Colbert, Levary and Shaner, 2000]. As both generic Masters Programs and more specialized programs grow as a proportion of such programs in the education market, it has become increasingly important that they are evaluated for quality (Lado, Cardone and Rivera, 2003).

Masters programs must meet the demands of both students and the companies that employ graduates of the programs (stakeholders). Education and training are services provided to the student. Therefore, the success of a program will depend on a large extent to its market orientation and on the quality and degree of satisfaction experienced by the student. Marketing research on quality of service and customer satisfaction is especially useful in this context.

There are research studies that prove the applicability of:

- factor analysis techniques for analyzing the motivations of university students [Juric, Tood and Henry, 1997];
- cluster analysis to analyze student profiles [Stafford, 1994];
- multidimensional scales for evaluating performance in a faculty [Herche and Swenson, 1991];
- conjoint analysis to design the course offering [Dubas and Strong, 1993]; analyses of repositioning of universities and of their Masters programs [Goldgehn and Kane, 1997; Comm and LaBay, 1996].

A dominant trend in education is based on the idea that students and their potential employers may be treated as market segments with expectations that educators must strive to know and satisfactorily meet [Anderson, Summey and Summey, 1991; Kotler and Fox, 1997; Colbert, Levary and Shaner, 2000].

The interest in quality in high education (basically in university) is not new (Peña 1997). In the last years, as a reflection of the growing importance of quality in the corporate world and in academic research, corporate and academic concepts and methods have been extended to the public sector and university education. Experimental programs to encourage quality in university teaching are being advocated in the European Union (EHEA), and in Spain the Ministry of Education and Science (ANECA) has promoted a program that is now in effect. According to Peña, these initiatives are based on the hypothesis that the perspective and methods of quality improvement in the business world are applicable to university teaching.

Having defined above the concept of the student as customer in order to measure its qualities, we must now consider the concept of product/service in university education. According to the *European Foundation for Quality Management* (EFQM), the product is defined in terms of value added to the student's knowledge, skills and personal development. As with the corporation, the quality of the product is linked to the quality of the industry process. Therefore, assessing the quality of the product in teaching entails analyzing the quality of the educational processes and identifying its key elements. The quality of the faculty is a particularly important key factor in Barnett's (1992) proposed integrative model.

Student satisfaction is generally measured by periodic surveys. While the use of surveys as instruments for measuring student evaluation of teaching has given rise to some controversy, [Simpson and Siguaw, 2000] shows they are systematically used by 98% of universities and 99% of business schools in the United States. These authors report that teachers have perceived certain weaknesses in the surveys and have developed different practices to influence these evaluations. Therefore, it is important to have and use complementary evaluative instruments. Authors such as Murphy (1999) propose independent evaluation. The institutions that use this method delegate the task of making unannounced observation visits to classes to another teacher at the same level.

Despite the criticism levelled at the survey system, its utility as a measuring tool is widely recognized [Greenwald, 1997; McKeachie, 1997; Cashin and Downey 1992; Guolla, 1999]. A review of the most widely used questionnaires can be found in Guolla (1999). A revision of the literature on student evaluation of teachers can be found in Marsh (1987, 1993, 1994).

This paper is organized as follows: Chapter 2 presents a methodology in which the weights are estimated from the observed relationship between the student's evaluations of overall quality and the evaluations of the attributes by a nonparametric procedure. Also, summarizes computer results and discusses the problems with previous approaches to estimate the weights in the quality service measurement. Chapter 3 describes the application of the methodology presented for measuring the quality of postgraduate education in a Spanish Public University. Finally, Chapter 4 presents the main conclusions and discusses avenues to future research.

1.1. Notation and Problem Definition

Suppose that we have a population of students. This population includes our current students, and it could also include future or potential students and former students. We assume that the size of the student's population, N, is large. Let us call Q_i to the perceived quality of a given service by the i_{TH} student from this population. The student compares his expectations towards a certain service with its perceived performance (see Parasuraman et al., 1988, 1991, 1994a, 1994b; Zeithaml et al., 1990). The judgment of quality is built up on the basis of this theoretical construct. Good service quality evaluation develops when perceptions exceed or are equal to expectations. Consequently, most approaches try to measure this gap directly (Liljander and Strandvik, 1993).

On the other hand, the models explaining quality use the concept of importance (Hüttenrauch 1994, Behrens, Schneider and Weisberg 1978). The student determines all characteristics he expects the ideal service to receive. Because not all of them are equally important, he weighs the importance of each. He builds his quality judgment on his perception of each characteristic multiplied with its specific significance. Summing up all evaluated criteria gives the total quality score (ISO 26362: 2009).

In the literature, it is common to assume that student's evaluation will be a function of several attributes $X_1,\ldots,X_k$ which determine the global evaluation of the service. Let us call $X_{i1},\ldots,X_{ik}$ to the evaluations of these attributes made by the i_{TH} student. Then,

$$Q_i = f\left(X_{i1},\ldots,X_{ik}\right). \tag{1.1}$$

Notice, that f is common to all the students.

A linear quality indicator (Behrens, Schneider and Weisberg 1978) assume that the function (1.1) can be approximated by

$$Q_i = \sum_{j=1}^{k} w_j X_{ij}, \tag{1.2}$$

where the coefficients w_j are weights, so that they must be positive and they must add up to one:

$$\begin{aligned} &w_j \geq 0 \qquad \forall j \\ &\sum_{j=1}^{k} w_j = 1 \end{aligned} \tag{1.3}$$

These weights can be considered as measures of the relative importance of attribute X_j in determining the evaluation of the quality of the service for all the students.

In our approach, we design a specific quality function for each student and to calculate the importance that each student assigns to each quality attribute of the academic programme.

Thus, we define

$$Q_i = f_i\left(X_{i1},\ldots,X_{ik}\right), \tag{1.4}$$

Notice, that f_i is specific for each student. This is the main and crucial difference with classical models

As a consequence, we can calculate a linear approximation of f_i given by

$$Q_i = \sum_{j=1}^{k} w_{ij} X_{ij}, \tag{1.5}$$

where the coefficients w_{ij} are specific and individual weights for each student, so:

$$\begin{aligned} &w_{ij} \geq 0 \qquad \forall i, \forall j \\ &\sum_{j=1}^{k} w_{ij} = 1 \quad \forall i \end{aligned} \tag{1.6}$$

It is important to remark that, in the classical approach we had k weights, that is, $w_1, \ldots, w_k$. With our approach we have $n \ x \ k$, that is, k weights per student.

In this article, part of our effort is dedicated to present and develop a methodology to calculate the weights considering that different students may have different weights for the attributes.

1.2. Methods to Determine the Weights. Classical Tools

Several methods of measuring service quality have been developed and discussed over the last few years. Reviewing the service quality literature, most of these models work with expectations (see Parasuraman et al., 1988, 1991, 1994a, 1994b; Zeithaml, 1988).

Expectations are already integrated in the evaluation of the perceptions. When a student judges a certain characteristic to be good, he/she expresses that it exceeds either his/her predictive or his/her service expectations. However, the student often has only a vague idea about the latter. For this reason, the measurement of expectation had been rejected. Instead, it is common to work with the perceptions and the importance of the attributes.

We assume a linear quality indicator from the function (1.6) and we assume that the weights w_{ij} used by the i_{TH} student for the j_{TH} attribute are independent of the evaluation made by this student for this attribute X_{ij}. The justification of this assumption is that the evaluation of an attribute represents how the level of service in this attribute compares to an ideal or standard performance. For instance, suppose that the service is a restaurant at the university and the attribute is the speed of the service measured by the time the student has to wait to receive his order. Then, the evaluation of the waiting time depends on previous experiences of the student on similar situations and will normally depend on the type of restaurant. We assume that the evaluation of this attribute in a particular restaurant is independent from the importance that the speed in the service has in his judgment of the quality of the service.

We define the service quality as the expected value of Q_i in the student's population

$$Q = \frac{\sum_{i=1}^{N} Q_i}{N} \ . \tag{1.7}$$

The service quality can readily be obtained from equations (1.7) by using the independence of the variables w_{ij} and X_{ij}. Then this global measure of service quality will be given by:

$$Q = \sum_{j=1}^{k} E[w_{ij}] \ E[X_{ij}] = \sum_{j=1}^{k} w_j m_j , \tag{1.8}$$

where we have called m_j to the average evaluation of attribute j_{TH} in the population, and w_j is the mean of the distribution of the weight of this attribute in the population.

The estimation of service quality can be obtained from (1.7), by taking the average of the evaluation provided by a sample of students, or by (1.8), by estimating the mean weights of each attribute in the population and the average of the evaluations for the attributes. Although both procedures must lead to the same final number, the quality index model (1.8) provides a decomposition of the sources of the service quality with the following advantages:

(1) A quality index allows comparing the average value of the attributes of our service to the values of other companies and can reveal our relative strengths and weaknesses in a SWOT analysis.
(2) Knowing the attribute weights allows the ordering of the attributes according to their relative importance to the student, showing the key factors in order to improve quality.
(3) Students can be segmented by their weighting function, obtaining a market segmentation function directly linked to our quality objectives.
(4) If the attributes can be related to some objective measures of performance it is possible to substitute the subjective evaluations of the attributes by objective measurements, allowing a simple monitoring of the quality index.

The objective of many quality evaluations is to build a quality index (scalar measure) to summarize the performance of the service. Reduction of all the dimensions of an evaluation to a single number can be subject to many criticisms. However, the presence of one quality index is required for decision making.

The operational definition of service quality presented has some limitations. First, we may have a good service quality on average, but a very bad service quality for some groups of students. This may happen either in two ways:

- Because some segments of the students have a very different weighting function for the quality attributes, we call this situation “implicated population”,
- Because they have a different evaluation of the attributes, we call this situation “explicated population”.

These two situations should be identified because we can provide a better service if we identify clusters of students with different values or opinions about quality. Then, it is more informative to measure service quality in these different populations.

It must be remembered that the mean is only a good descriptive measure when we have an homogeneous sample and that it can be non representative when the data comes from a mixture of very different populations.

1.3. Evaluation of the Weights

For indirect evaluation of the attributes and the quality from a sample of experts from some population of experts, members of a representative sample. The weights are obtained by statistical analysis.

There are two ways to do so:

a) Fix the values of the attributes and ask for a global evaluation (value of Q). Then fit a linear model and determine the weights. This is conjoint analysis; and then we can use fractional factorials to build a model and estimate the weights (Gustafsson, 2007).
b) To evaluate both the attributes and the global performance (or global quality) and then use several linear regression methods to build a model and estimate the weights (i.e. Generalized Least Squared Method).

2. Proposed Methodology

In order to deploy this quality model we need:

- The complete list of attributes.
- The weights.

The most important part is to obtain the weights, because we can always write a long list of attributes but some of them may have weights equal to zero.

Initial hypothesis:

HH1: There is exists a function $f_i \mid f_i(X) = Q_i$ for each i.

Then, our model is locally $w_i^T X \approx Q_i$, because $w_i^T X$ is a linear approximation of f_i. So, we can define the matrix

$$W = [w_1, \ldots, w_k] = \begin{bmatrix} w_{11} & \cdots & w_{1k} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nK} \end{bmatrix}$$

Definition 1: ε-reasonable neighbours

Given an element X we will say that y is an ε-reasonable neighbour if $y \in B(X, \varepsilon)$, where ε denotes the size of the neighbourhood (Silverman 1986)

Definition 2: Matrix of reasonable neighbours

Given an element X we will define l ε-reasonable neighbours, that is $X_{(1)}, \ldots, X_{(l)}$. Where $(1), \ldots, (l)$ is an appropriate rearrangement of the k indexes in the set $\{1, \ldots, n\}$ and $l \geq k$. Then, we will define X^i and Q^i as:

$$X^i = \begin{bmatrix} X_i \\ X_{(1)} \\ \vdots \\ X_{(l)} \end{bmatrix} = \begin{bmatrix} X_{i1} & \ldots & \ldots & X_{ik} \\ X_{(1)1} & \ldots & \ldots & X_{(1)k} \\ \ldots & \ldots & \ldots & \ldots \\ X_{(l)1} & \ldots & \ldots & X_{(l)k} \end{bmatrix}, \; Q^i = \begin{bmatrix} Q_i \\ Q_{(1)} \\ \vdots \\ Q_{(l)} \end{bmatrix}.$$

Remark:

Notice that we may build ε-reasonable neighbours not in the sample. For instance, given an element X, if $|\xi| < \varepsilon$, the element $X + \xi\varepsilon$ is an ε-reasonable neighbours.

Our aims is to estimate each component of the matrix W with the matrix

$$\widehat{W} = [\widehat{w}_1, \ldots, \widehat{w}_k] = \begin{bmatrix} \widehat{w}_{11} & \cdots & \widehat{w}_{1k} \\ \vdots & \ddots & \vdots \\ \widehat{w}_{n1} & \cdots & \widehat{w}_{nK} \end{bmatrix}:$$

The following algorithm describes in detail how to obtain $\widehat{W}$

Algorithm to estimate $\widehat{W}$

For each student $i = 1, \ldots, n$

Step 1.
Calculate its l ε-reasonable neighbours, that is $X_{(1)}, \ldots, X_{(l)}$.

Step 2.
Build X^i and Q^i:

Step 3.
Solve possible numerical redundancies in the matrix $[X^i | Q^i]$.

Step 4.
Estimate the vector w_i as $\hat{w}_i = [\widehat{w}_{i1}, \widehat{w}_{i2}, \ldots, \widehat{w}_{ik}]$, solving the systems $X^i \widehat{w}_i = Q^i$ using a least squares method with linear constraints.

Figure 2.1. Algorithm to estimate $\hat{w}_{ij}$

The proposed methodology presents several advantages respect to the “classical tools”:

A1: We can use parallel computation to solve the linear systems in the step 4 (Kepner 2009).

A2: When the decision maker needs a single index, a scalar measure to summarize the performance, we can define:

$$\overline{w_j} = \frac{\sum_{i=1}^{n} \widehat{w}_{ij}}{n} . \tag{2.1}$$

That reduction of all dimensions of an evaluation to a single number can be subject to many criticism, however, it may be required for decision making. It is an alternative use of the estimation of the weights and it provides an equivalent result to the one obtained using “classical methods”.

A3: We have estimated each component $\widehat{w}_{ij}$. Now, we can use any kind of multivariate method to determine new groups of students, such us a posterior student segmentation, and then to prepare inferences about it.

A4: We can work, then, directly with weights that each student assigns to each quality attribute. In fact, we don't accept the mean of the weights as a good representative estimator. It must be remembered that the mean is only a good descriptive measure when we have a homogeneous sample and that it can be very non representative when the data comes from a mixture of very different populations of students.

A5: We estimate the weights that each student assigns to each quality attribute with the information obtained from its similar students. We choose the set of "similarities" based on the nearest neighbourhood estimate.

A6: We define a vector of weights for each student; therefore we are implicitly defining the importance given by the student to each quality attribute. Notice that working with these weights as data we may define new relations among the data.

3. Computational Experiments

In this chapter, we present the results of applying AQM to measure the quality of several simulated data sets where we know the true value of the parameters of the model. Also, we present the results to measure the quality of the postgraduate courses of a public Spanish University.

AQM has demonstrated to be able to treat these kind of data. AQM permits to design a specific quality function for each student and to calculate the importance that each student assigns to each quality attribute of the academic programme.

3.1. Simulated Data Sets

We have experimentally evaluated several simulated examples. In this section we present the results of applying the AQM methodology to a simulated data sets (Driscoll, 2009; Van Loan, 2010), obtaining that AQM provides better performance than the existing methodologies (Hayes, 1998; Bober, 2009).

The comparison have been done using the mean quadratic error:

$$MCE = \frac{\sum_{i=1}^{n}\left[\sum_{j=1}^{k}\left(w_{ij} - \widehat{w}_{ij}\right)^{2}\right]}{n \times k}, \; i = 1,\ldots,n, \; j = 1,\ldots,k$$

where:

w_{ij} : true weight of student i_{TH} in the attribute j_{TH} .

$\hat{w}_{ij}$: estimated weight of student i_{TH} in the attribute j_{TH} .

We have generated data with the following characteristics:

- Four different groups providing completely different answers, population 1 and population 2, population 3 and population 4,
- One thousand students, two hundred and fifty students in each population,
- Five quality dimensions or attributes,
- Variables scale from 0 to 100, with one decimal point.
- Every student in the population 1 assigns approximately the following weights: w_{11} =0.2, w_{12} =0.2, w_{13} =0.2, w_{14} =0.2, w_{15} =0.2.
- Every student in the population 2 assigns approximately the following weights: w_{21} =0.3, w_{22} =0.4, w_{23} =0, w_{24} =0.1, w_{25} =0.2.

- Every student in the population 3 assigns approximately the following weights: w_{31}=0, w_{32}=0.2, w_{33}=0.3, w_{34}=0, w_{35}=0.5.

- Every student in the population 4 assigns approximately the following weights: w_{41}=0.5, w_{42}=0, w_{43}=0.4, w_{44}=0.1, w_{45}=0.

Using a traditional least squares method, we can estimate the following weights:

$\hat{w}_1$=0.2444, $\hat{w}_2$=0.2906, $\hat{w}_3$=0.1861, $\hat{w}_4$=0.1642, $\hat{w}_5$=0.1147

with $MCE \approx 0{,}3$

Our method, AQM, using a weighted Minkowsky metric and adaptive neighbourhood size, estimates the following weights:

	$\hat{w}_{11}$	$\hat{w}_{12}$	$\hat{w}_{13}$	$\hat{w}_{14}$	$\hat{w}_{15}$
Mean	0.223	0.197	0.261	0.196	0.123
Median	0.207	0.202	0.214	0.198	0.197
Mode	0.200	0.200	0.200	0.200	0.200

Table 3.1. Estimated Weights for population 1 by AQM

	$\hat{w}_{21}$	$\hat{w}_{22}$	$\hat{w}_{23}$	$\hat{w}_{24}$	$\hat{w}_{25}$
Mean	0.304	0.426	0.0601	0.1129	0.097
Median	0.305	0.402	0.000	0.105	0.200
Mode	0.300	0.400	0.000	0.100	0.200

Table 3.2. Estimated Weights for population 2 by AQM

	$\hat{w}_{31}$	$\hat{w}_{32}$	$\hat{w}_{33}$	$\hat{w}_{34}$	$\hat{w}_{35}$
Mean	0.062	0.212	0.302	0.045	0.379
Median	0.000	0.207	0.296	0.000	0.476
Mode	0.000	0.200	0.300	0.000	0.500

Table 3.3. Estimated Weights for population 3 by AQM

	$\hat{w}_{41}$	$\hat{w}_{42}$	$\hat{w}_{43}$	$\hat{w}_{44}$	$\hat{w}_{45}$
Mean	0.492	0.024	0.415	0.035	0.044
Median	0.494	0.000	0.411	0.097	0.000
Mode	0.500	0.000	0.400	0.100	0.000

Table 3.4. Estimated Weights for population 4 by AQM

$MCE \approx 10^{-3}$

Notice that AQM estimates accurately the weights to each population, leading to $MCE \approx 10^{-3}$. Notice that if we average the weights estimated by AQM, the results is similar to that obtained by the classical method.
In the following figure you can find the estimation of the weights.

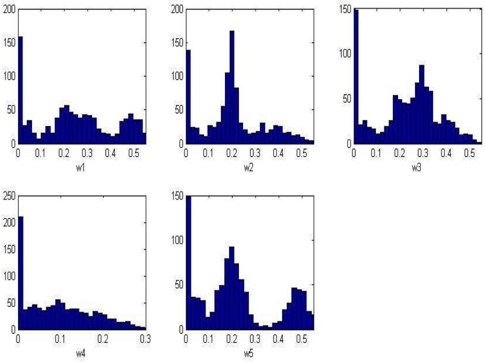

Figure 3.1. Estimated Weights by AQM

3.2. A real case

We have used a real data set collected from two postgraduate programs in a business school. We have used those data to find the weights that students assign to every dimension of the "service" (Bayo 2003). Our aim is to show that AQM is able to treat this kind of data.

Sample

The data were obtained from surveys conducted from the Masters programs developed by the Department of Business Administration of a Spanish Public University. Information was gathered from questionnaires on all the subjects taught and all the teachers who taught the subjects. Data from a survey carried out from 2003 to 2008, the unit of analysis was students of a Master of Business Administration (Spanish language version and English language version). A total of 5769 questionnaires were administered, and the number of valid questionnaires received was 4372. The questionnaires considered valid where those in which the respondent had answered all of the questions of interest, yielding a full set of variables used in the subsequent analysis (Derek, 2000; Everitt, 2001; Johnson, 2002; Chambers, 2005).

Data from survey have been classified by years, terms and type of the subjects:

- Years: from 2003 to 2008.
- Terms: T1, T2 y T3.
- Subject types: 2, 1 and 0; qualitative, quantitative and mixed subject, respectively.

In the following tables we can see the evolution of received questionnaires since 2003 until 2008, separated by years and academic year terms.

Year	T1	T2	T3	Total
2003-04	537	537	672	1746
2004-05	484	398	482	1364
2005-06	213	225	265	703
2006-07	146	376	371	893
2007-08	289	370	404	1063
Total	1669	1906	2194	5769

Table 3.5 Evolution of received questionnaires

The trend of the evolution of received questionnaires, in general, is negative.

Survey Instrument

The definitive questionnaire contained 12 questions that allowed us to measure the aspects detailed below:

P1. Interest: refers to the student's interest in the subject.
P2. Integration: integration degree of the subject in the master.
P3. Satisfaction with teacher: overall student satisfaction with the teacher.
P4. Clarity: the teacher teaches clearly.
P5. Punctuality: the teacher is on time.
P6. Prom Participation: the teacher promotes participation in class.
P7. Bibliography: the usefulness and interest of the readings and recommended bibliography.
P8. Utility: the usefulness of the teaching assistant practice lessons.
P9. Satisfaction Assistant: overall student satisfaction with the teaching assistant.
P10. Equilibrium: comparison between practice contents and theory contents.
P11. Output Level: Output level reached in the subject.
P12. Input Level: Input level previous to the subject.

All measures were registered on a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree."

3.2.1 Preliminary results

In the following tables we can see descriptive aggregated results. Table 3.5 shows results by questions. Table 3.6 shows results by questions and subject type:

	Mean	Mode	Median
P1	3,95	5	4
P2	3,91	5	4
P3	3,69	4	4
P4	3,60	4	4
P5	4,25	5	5
P6	3,66	5	4
P7	3,43	4	4
P8	3,45	4	4
P9	3,20	4	4
P10	3,37	3	3
P11	3,52	4	4
P12	3,12	4	3

Table 3.5 Descriptive statistics for aggregated results

Globally speaking, P5 Punctuality, has obtained the best result (maximum possible mode and median and mean over than 4.2 points).

		0	1	2
P1	Mean	4,15	4,05	4,22
	Median	4	4	4
P2	Mean	4,08	4,02	4,22
	Median	4	4	4
P3	Mean	3,91	3,83	4,00
	Median	4	4	4
P4	Mean	3,81	3,69	3,95
	Median	4	4	4
P5	Mean	4,47	4,45	4,42
	Median	5	5	5
P6	Mean	3,83	3,76	4,03
	Median	4	4	4

P7	Mean	3,70	3,65	3,79
	Median	4	4	4
P8	Mean	3,77	3,71	3,94
	Median	4	4	4
P9	Mean	3,84	3,69	3,91
	Median	4	4	4
P10	Mean	3,69	3,61	3,69
	Median	4	4	4
P11	Mean	3,78	3,66	3,88
	Median	4	4	4
P12	Mean	3,40	3,28	3,54
	Median	4	3	4

Table 3.6 Descriptive statistics for aggregated results, by type subjects

Globally speaking, for results by subject type, P5 Punctuality, has obtained the best result (maximum possible mode and median and mean over than 4.4 points).

In the following table we can see aggregated results by options of the *Likert scale*:

	0	1	2	3	4	5
P1	3,7%	2,2%	4,0%	15,2%	35,3%	39,7%
P2	4,2%	1,7%	4,3%	16,1%	35,8%	37,8%
P3	4,4%	3,4%	6,9%	20,0%	34,0%	31,2%
P4	4,4%	4,7%	9,0%	20,6%	30,9%	30,3%
P5	4,6%	0,9%	2,7%	8,9%	23,0%	59,9%
P6	4,7%	3,6%	7,4%	20,9%	31,7%	31,7%
P7	7,1%	3,1%	9,2%	24,5%	33,1%	23,0%
P8	8,6%	4,2%	8,0%	19,6%	31,9%	27,7%
P9	14,9%	4,3%	6,8%	19,0%	30,1%	24,9%
P10	6,9%	4,0%	5,1%	37,6%	22,1%	24,2%
P11	5,2%	3,0%	6,6%	24,3%	41,7%	19,2%
P12	6,0%	8,1%	12,5%	28,3%	31,3%	13,8%

Table 3.7 Descriptive percentages for aggregated results

Globally speaking, for results by options of the *Likert scale*, P5 Punctuality, have obtained the best result (approximately 60% of the questionnaires with maximum possible opinion).

Hierarchical cluster analysis

We have done a correlation analysis and a hierarchical cluster analysis by variables.

In the following figure we can see the dendrogram for aggregated data:

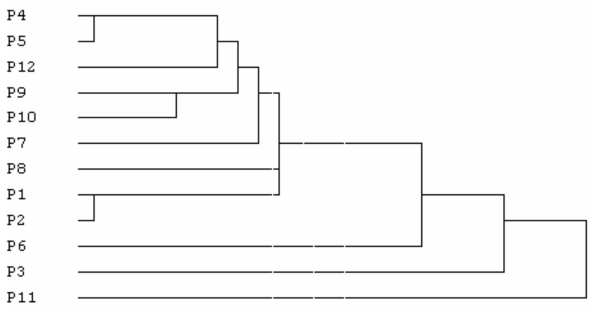

Figure 3.2 Dendrogram for aggregated data

The dendrogram shows strong similarity between:

- P4 - P5
  P4 *Clarity* and P5 *Punctuality* of the teacher.
- P1 – P2
  P1 *Interest* in the subject and P2 *Integration degree* of the subject in the master.
- P9 – P10
  P9 *Satisfaction with the teaching assistant* and P10 *Equilibrium* between practice contents and theory contents.

Globally speaking, students have a mature opinion referent to the subjects. The first cluster measures “Profesionality/Expertise” of the teacher. The second one measures “previous attitude of the student”. The third one measures “the work of the teaching assistant”.

3.2.2 New findings using AQM

In the following section we present the results of applying AQM methodology to the data set. The goal is to determine the relative importance of each explicative variable (P1, P2, P4, P5, P6, P7, P11 y P12) to explain the response variable “P3. Satisfaction with teacher”. Variables related to “Teaching assistant” (P8, P9, P10) have been eliminated of the analysis.

Hierarchical cluster analysis
We have done a correlation analysis and a hierarchical cluster analysis by the weight variables.
Correlation analysis does not show important values. Remember that correlation coefficient only detect linear relationships between variables.

In the following figure we can see the dendrogram for weights variables for aggregated data:

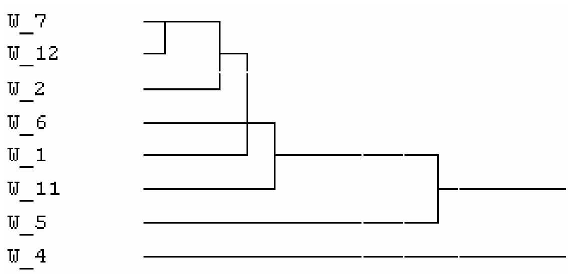

Figure 3.3 Dendrogram for weights variables

Dendrogram shows strong similarity between:

- W7 – W12
  W7 The usefulness and interest of the *readings and recommended bibliography*.
  W12 *Input level previous to the subject*.

We can say, that the cluster measures "Didactic materials" (in reference to the level of student).

Factorial analysis for P's and W's
We have done a factorial analysis for the explicative variables (P) and the weights variables (W). Explicative variables (P) were scaled up to one.

Two factors have been detected, they explained 90,993% of the total variance. Factor 1 (factor score 1) measures the mean of the variables. Factor 2 (factor score 2) faces theory lessons versus practice lessons.
In the following figure we can see explicative and weights variables by factors variables:

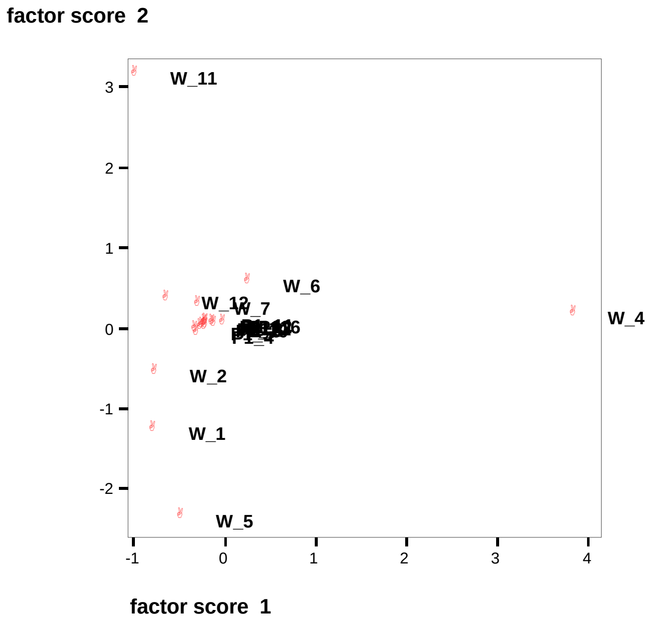

Figure 3.4 Explicative and weights variables

Figure shows a big distance between W11, W4 and W5 and the rest of the variables.

Factorial analysis for W's
We have done a factorial analysis for the weights variables (W).
Two factors have been detected, they explained 39,138% of total variability. Factor 1 (factor score W 1) measures the mean of the variables. Factor 2 (factor score W 2) faces theory lessons versus practice lessons. The distance between W4 and W11 and the rest of the weight variables. Weight variables W7 and W12 are similar to each other.

Factorial analysis for P's

We have done a factorial analysis for the explicative variables (P). Explicative variables (P) were scaled up to one. Two factors have been detected, they explained 37,201% of total variability. Factor 1 (factor score P 1) measures the mean of the variables. Factor 2 (factor score P 2) faces theory lessons versus practice lessons.

In the following figure we can see explicative variables by factors variables.

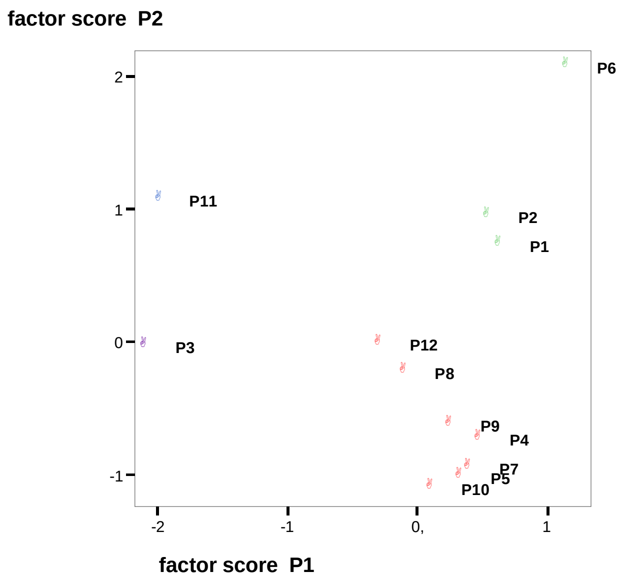

Figure 3.5 Scaled explicative variables

Figure 3.5 shows a big distance between P6, P11 and P3 and the rest of the variables. Variables P1 and P2 are similar to each other.

Weights variables (W's) versus Overall Quality (P3)
In the following figures we can see the relationship between weights variables (W's) and variable P3.
In the figures above we can conclude that "the students that assign high importance then to some attribute then assign high qualifications". In general, there is no answers with high weights (W's) and low overall quality (P3). The opposite fraise in not true.

Results by subject types
In the figures 4.18, 4.19 and 4.20 we can see the results of weights in the complete data set, MAE and MBA program together by subject types 2, 1 and 0, respectively:

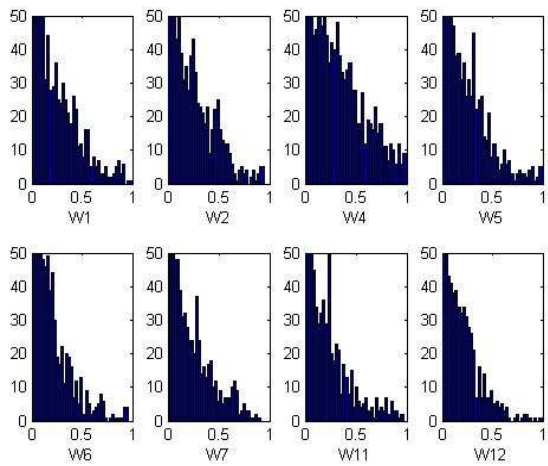

Figure 3.7 Weights for aggregated data set, subject types 2

Weights present a big variability, ranging from 0 to 1 with Standard deviation equal to 0.228. The multivariate analysis has detected three clusters (Mardia 1979, Gordon 1989), both programs show a dissimilar behaviour:

- The first cluster is composed by MBA students.
- The second cluster is composed by low level values in P1 (interest) MAE students.
- The third cluster is composed by high level values in P1 (interest) MAE students.
-

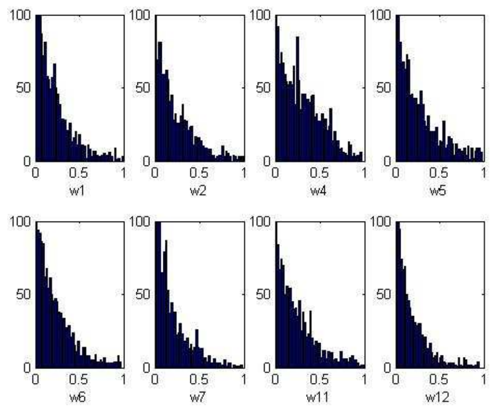

Figure 3.8 Weights for aggregated data set, subject types 1

Weights present a big variability, ranging from 0 to 1 and standard deviation equal to 0.186. The multivariate analysis has detected two clusters, both programs show a similar behaviour:

- The first cluster is composed by low level values in P1 (interest) students.
- The second cluster is composed by high level values in P1 (interest) students.

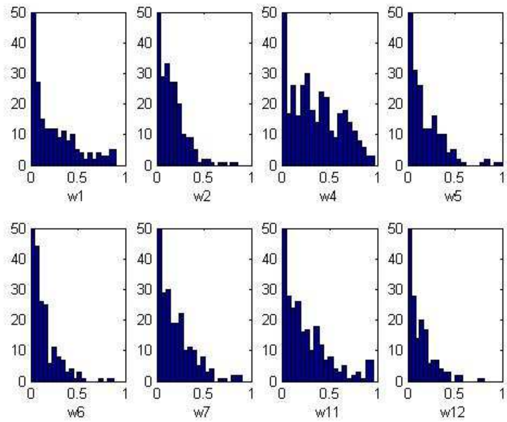

Figure 3.9 Weights for aggregated data set, subject types 0

Weights present a big variability, ranging from 0 to 1 and standard deviation equal to 0.197. The multivariate analysis has detected two clusters, both programs show a similar behaviour:

- The first cluster is composed by low level values in P1 (interest) students.
- The second cluster is composed by high level values in P1 (interest) students.

4. Conclusions

AQM was applied to measure the quality of the education at postgraduate department of a Public university.

The data were obtained from surveys conducted from the Masters programs developed by the Department of Business Administration of a Spanish university. Information was gathered from questionnaires on all the subjects taught and all the teachers who taught the subjects. Data from a survey carried out from 2003 to 2008, the unit of analysis was students of two master programs of a business school: A total of 5769 questionnaires were administered, and the number of valid questionnaires received was 4372. The questionnaires considered valid were those in which the respondent had answered all of the questions of interest, yielding a full set of variables used in the subsequent analysis.

Data from survey have been classified by years (from 2003 to 2008), terms (T1, T2 and T3) and type subject (2, 1 and 0; qualitative, quantitative and mixed subject, respectively).
We have used those data to find the weights that students assign to every dimension of the "service". Results were satisfactory; ALR is able to treat this kind of data.
New relationships were discovered (for instance, W7 and W12). Also, relationships between W's variables and P3 were discovered.

For example, in the following figure we can see this kind of relationships:

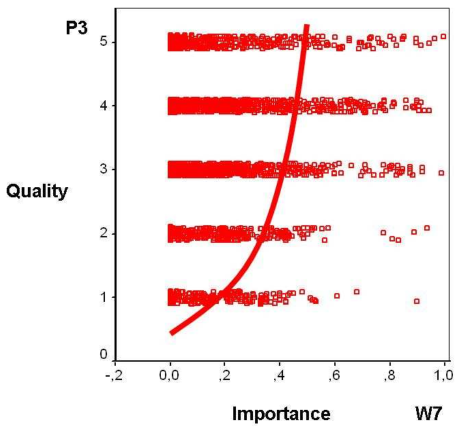

Figure 4.1 Relationship Importance - Quality

The knowledge of the relative importance that the students give to the quality attributes that determines the global service quality is key for any process of service quality improvement.
Several methods of measuring service quality have been developed and discussed over the last few years. Reviewing the service quality literature and the operational definition of service quality based on the mean of the weights have some limitations.

First, we may have a good service quality on average, but a very bad service quality for some groups of students. This may happen either in two ways:

- because some segments of the students have a very different weighting function for the quality attributes, we call this situation "implicated population"
- because they have a different evaluation of the attributes, we call this situation "explicated population".

These two situations must be identified because we can provide a better service if we identify clusters of students with different values or opinions about quality. Then, it is more informative to measure service quality in these different populations.

It must be remembered that the mean is only a good descriptive measure when we have an homogeneous sample and that it can be very non representative when the data comes from a mixture of very different populations.

The procedure presented in this work seems to be a useful way to estimate the implicit weights used by each student in his overall evaluation of service quality.

Concluding Remarks

In this work we have discussed several techniques for measuring the Quality of Service (QoS). We have also presented a new methodology (AQM) for it based on non parametric statistics.

We have extended our efforts towards three directions:

- First, we have adapted a definition of dissimilitude between data.
- Second, we have developed the necessary linear algebra for solving several numeric problems present in the real world.
- Third, we have calibrated and validated the method.

The method we propose have several general advantages:

- It is simple: because it is based on a typical instrument of measurement that the students are familiar with.
- It is versatile: because it is useful for measuring Quality, Loyalty Student, Recovery Student, among others.
- It is economic: because it can be applied for any number of attributes and/or sample size.
- It is transparent: because it is based on statistical model and linear algebra and can be tested and checked (validated) with the simulated data.
- It is efficient: because it works well in all the simulated cases we have considered.
- Also, it is very easy for programming.

And, particularly, the methodology presented in this work has the following advantages:

- Knowledge of the attribute weights allows the ordering of the attributes according to their relative importance to the student, showing the key factors for improving quality.
- Student weights can be related to student characteristics to make market segmentation directly linked to quality objectives. The characteristics of the students and the market segmentation of our service can be obtained by comparing their mean weights to those of the students of other services.
- The relative strengths and weaknesses of the service can be determined by comparing the mean value of the attributes of the service to the values of other companies (Benchmark process or SWOT analysis).
- Also, when the attributes of the service quality can be related to some objective measures of performance; it is possible to substitute the subjective evaluations of the attributes by objective measurements, allowing a simple monitoring of the quality index and of their components by Control Charts. In this way, we can use many of the techniques developed for the control of product manufacturing to the improvement of service quality, as Statistical Process Control (SPC).

We have implemented and validated our methodology in several simulated datasets with interesting results. It was very important for calibrating the linear algebra and the different parameters of the methodology. We have implemented our methodology to measure dates from two real cases.

5. Future Research

We have also identified several directions towards future work:

- Latent Variables: *We will study the possibility to allow that students, in their evaluations of the overall quality, may be taking into account some attributes not considered in the model:*
- Nonlinearity and Interaction: *We will study models which are able to deal with nonlinearity and interaction between attributes* (Ravi, Warren and Jos, 2002).
- Variability in the Distribution of the Attribute Coefficients: *In addition to estimating the mean of the coefficients, we will also analyze the role of the variability in the distribution of the index in the student's population.*
- Bayesian Models: *We will study Bayesian models:*
- Parallel Computation: *We will study and will implement the quality model by parallel algorithm.*
- Computational Improvement: *We will study the linear algebra requirement of the quality model; in particular, we will economize the resolution of the linear equation system and/or the least squared system.*
- Long Term Studies: *We will study the application of time series in the quality mode:*
  A typical family of projects is characterized by: long term duration, a succession of several planning phases, a constant change of internal student, at least, one in each phase
  For this kind of family of projects we will research the adaptation of the methodology deployed in this article.

- Applications and Extensions of the Model: *We will research the possibility of measuring in other fields of the knowledge and with other variables.*

We have developed a methodology for measuring quality service and we have presented its advantages in several examples and in a real case. This methodology is useful for any number of attributes and for any sample size. We will try to extend the methodology to other fields as:

- Marketing: loyalty (Caruana 2002), fidelity plans, student recovery (Olsen 2002),
- Human resources: labour clime,
- BSC: implementation of the Balanced Scorecard,
- ISO: implementation of quality systems under ISO 9001 (point 8.2.1),
- EFQM: deployment of EFQM model (key results criteria, people results, student results, society results, etc.).

6. Acknowledgments

We would like to thanks to RIESGOS-CM project, Ref. CAM s2009/esp-1594, funded by the Government of Madrid and EDUCALAB project, Ref. IPT-2011-1071-430000, funded by the Spanish ministry of Science and Innovation.

We also would like to thank the Spanish Ministry of Education and Science (General Directorate of Research Projects, ECO2010-17158) and the Regional Government of Andalusia (Project of Excellence P09-SEJ-4467) for their financial support.

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